12th International Conference on Information Fusion
Seattle, WA, USA, July 6-9, 2009

A Geometric Feature-aided Game Theoretic Approach to Sensor Management

Xiaokun Li, Genshe Chen
DCM Research Resources LLC
Germantown, MD, U.S.A.
xli@dcmresearchresources.com
gchen@dcmresearchresources.com

Erik Blasch, Jim Patrick
AFRL, WPAFB,
Dayton, U.S.A.
Erik.blasch@wpafb.af.mil
James.patrick@wpafb.af.mil

Chun Yang
Sigtem Technology Inc.
San Mateo, CA, U.S.A
Chunyang.sigtem@sbcglobal.net

Ivan Kadar
Interlink Systems Sciences, Inc,
Lake Success, NY, USA
ikadar@SystemsSciences.com

Abstract - *Given the single-point node failure limitation of centralized sensor management schemes, decentralized sensor management (DSM) techniques are increasingly important for a simultaneous tracking and identification system. DSM options are realizable with the support of modern systems through increased bandwidth, wireless communication, and enhanced power, but require novel strategies to address constraints imposed by a large number of users Since game theory offers competitive models for distributed allocations of surveillance resources and provides mechanisms to handle the uncertainty of a surveillance area, we propose an agent-based negotiable game theoretic sensor management (ANGSm) approach. By incorporating subgame Nash Equilibrium into negotiation, all agent's needs are considered. With the DSM scheme, sensor assignment occurs locally, and with no central node, DSM reduces the risk of whole-system failures. To make the ANGSm approach more efficient and practical, a geometric feature, the range between a target and a sensor, is also incorporated in the bargaining strategy during sensor assignment. Simulation results of the geometric feature-aided game theoretic (GFGT) approach demonstrate the applicability of the proposed approach.*

Keywords: Distributed sensors, sensor management, agent based negotiation, game theory.

1 Introduction

Sensor management (SM) plays an important role in a simultaneous tracking and identification (STID) with multiple sensors to improve tracking performance by combining the measurements of multiple sensors. According to [1], SM can be treated as a general strategy that controls sensing actions, such as sensor assignment and sensor mode selection, to maintain the performance of target tracking while balancing resources when new targets are detected. Since sensing resources are generally limited, SM must solve an optimization problem that coordinates sensor resources to satisfy the tracking metrics of each target tracked. The input for a SM module could be target state estimate or its error covariance from the tracking module as well as target features/IDs classification module. The output of the SM could be sensor-target assignment and schedule of sensing actions.

The focus of the current SM strategies is mainly on *sensor assignment* and some of them are centralized sensor management (CSM) schemes [2, 3, 19]. For CSM, all sensor information, sensor assignment, and sensor scheduling are stored and completed in one central processing unit to achieve global optimum for sensor assignment. The advantages of using a CSM strategy include a simple system design and less computational load in a small scale network. However, CSM approaches are not always suitable for modern sensing/signal processing systems. When the scale of a system grows, the process of collecting information from all other sensors will be time consuming and undependable. Most importantly, when a sensing system works in a severe environment, the failure of the central node would cause the failure of the whole system.

To overcome shortcomings of centralized sensor management, *decentralized (DSM) approaches* have become increasingly important [6-9]. In the DSM schemes, instead of using only one central node for SM, some distributed processing nodes would generated and used to collect the information of sensors, targets, and/or environments, and then assign these sensors to different targets based on such information. DSM is more realistic for security and defense applications as the system would be frequently utilized in some complex areas and situations, such as in an environment with critically low signal-to-noise ratios or even dangerous areas. In such cases, it is not easy for a centralized approach to obtain the information from all the sensor nodes as some communication links might be broken at an unexpected time. Also, CSM system failure caused by the failure of one single node makes it not robust. Some DSM approaches (e.g. [10-12]), proposed more than ten years ago, coordinate locally (not globally) and there is no central node which will make any global decisions. The DSM advantages include a decentralized strategy can construct a scalable, modular, and survivable sensor network system. But the tradeoffs of DSM approaches include local optimum on sensor assignment and increased communication load for sensor network. With the support of modern systems through increased bandwidth, wireless communication, and enhanced power; DSM becomes more

Report Documentation Page

Form Approved
OMB No. 0704-0188

1. REPORT DATE **JUL 2009**	2. REPORT TYPE	3. DATES COVERED **06-07-2009 to 09-07-2009**

4. TITLE AND SUBTITLE **A Geometric Feature-aided Game Theoretic Approach to Sensor Management**	5a. CONTRACT NUMBER
	5b. GRANT NUMBER
	5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)	5d. PROJECT NUMBER
	5e. TASK NUMBER
	5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) **DCM Research Resources LLC, , ,Germantown,MD**	8. PERFORMING ORGANIZATION REPORT NUMBER
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)	10. SPONSOR/MONITOR'S ACRONYM(S)
	11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release; distribution unlimited

13. SUPPLEMENTARY NOTES
See also ADM002299. Presented at the International Conference on Information Fusion (12th) (Fusion 2009). Held in Seattle, Washington, on 6-9 July 2009. U.S. Government or Federal Rights License.

14. ABSTRACT
Given the single-point node failure limitation of centralized sensor management schemes, decentralized sensor management (DSM) techniques are increasingly important for a simultaneous tracking and identification system. DSM options are realizable with the support of modern systems through increased bandwidth, wireless communication, and enhanced power, but require novel strategies to address constraints imposed by a large number of users Since game theory offers competitive models for distributed allocations of surveillance resources and provides mechanisms to handle the uncertainty of a surveillance area, we propose an agentbased negotiable game theoretic sensor management (ANGSm) approach. By incorporating subgame Nash Equilibrium into negotiation, all agent?s needs are considered. With the DSM scheme, sensor assignment occurs locally, and with no central node, DSM reduces the risk of whole-system failures. To make the ANGSm approach more efficient and practical, a geometric feature, the range between a target and a sensor, is also incorporated in the bargaining strategy during sensor assignment. Simulation results of the geometric featureaided game theoretic (GFGT) approach demonstrate the applicability of the proposed approach.

15. SUBJECT TERMS

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT **unclassified**	b. ABSTRACT **unclassified**	c. THIS PAGE **unclassified**	**Public Release**	**8**	

workable for a sensor network. Developing decentralized management technique [14, 15] is becoming an active research area because of the complex arenas of sensor deployments.

2 Game Theoretic SM

Sensor assignment, the major task of sensor management, aims to control the data acquisition process in a multi-sensor system to enhance the performance of target tracking. In a decentralized sensor management (DSM) scheme, in order to protect the benefits of all parties in the sensor assignment, negotiation between them is necessary. Since game theory will protect the maximum interest of every party via competition and learning during negotiation, in this paper we propose an agent-based negotiable game theoretic sensor management approach (ANGSm) method which is based on a *geometric feature-aided game theoretic* (GFGT) scheme for decentralized sensor assignment to deal with the performance requirements of a dynamic environment.

2.1 Agent-based sensor assignment

For agent-based sensor assignment as illustrated in Fig. 1, each agent will represent a specific target according to the results of mission planning. All desired performance matrices and requirements of target tracking are stored in the agent and sent out via the agent. After the negotiations between any two agents, the available resources (sensors) are reallocated to different targets for optimum tracking performance to all agents. Adding a new agent or deleting an existing agent to the system will not affect the other agents. Each agent plays a management role to its own tracking tasks and negotiates to get the most available resources to satisfy its tracking tasks. The agents for multi-target tracking are generated dynamically and target-oriented. Once a target is found, an agent will be created accordingly and a SM module will be activated and executed. The SM module can be part of the data fusion tracker which is in charge of tracking a newly-found target, or runs independently of another processor, but should be in the carrier/platform and coordinates closely with the tracker.

According to the tracking requirements (i.e. current tracking situation/performance requirements and target states), an agent will *ask* for more resources (sensors) from other agents located in the same carrier/platform or on different carriers/platforms when necessary, or *reassign* some its own resources (sensors) to other agents when receiving proposals from others. Once the tracking task for the target has been completed, the agent will be dismissed and the SM module for this agent will be terminated. All resources of this agent will be released. For an agent-based multi-target tracking system, agents will be created and located in different carriers/platforms. If one carrier/platform is attacked and damaged, the agents in other carriers/platforms will continue to work without receiving any notification of the loss.

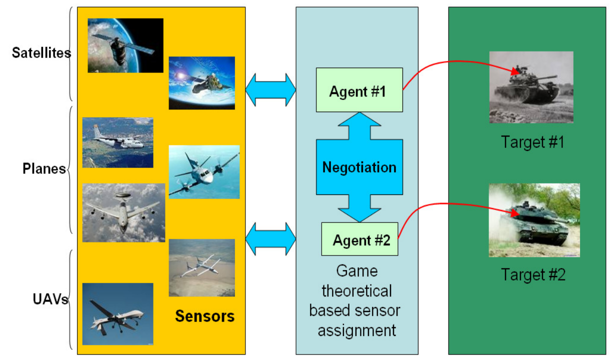

Fig. 1: Illustration of sensor assignment for two-target case

2.2 Game theory for sensor assignment

A fundamental concept in game theory is the ***Nash Equilibrium*** [15], which is named after John Forbes Nash, who first proposed it. The concept is a solution concept of a game involving two or more players. In the game, each player is assumed to know the equilibrium strategies of the other players, and no player has anything to gain by changing only his or her own strategy. If one player has chosen a strategy and no other player can benefit by changing his/her strategy while the other players keep theirs unchanged, then the current set of strategy choices and the corresponding payoffs constitute a Nash Equilibrium. In a Nash Equilibrium, each player must answer negatively to the question from others and knowing the strategies of the other players, and trying to benefit himself/herself from the strategies of the other players. For example, Tom and Jim are in game with Nash equilibrium, when Tom is making the best decision he can, and at the same time taking into account Jim's decision, Jim is also making the best decision he can, while taking into account Tom's decision. In the same way, many players are in game with a Nash Equilibrium if each one is making the best decision that they can, while taking into account the others. Each strategy in a Nash Equilibrium is a best response to all other strategies in that equilibrium. The Nash Equilibrium may sometimes appear non-rational in a third-person perspective as a Nash Equilibrium is not global optimal. The Nash Equilibrium may also have non-rational consequences in sequential games because players may "threat" each other with non-rational moves.

However, in many cases all the players might improve their payoffs if they could somehow agree on strategies different from the Nash equilibrium, which leads the concept of ***Subgame Equilibrium*** [17]. Subgame Equilibrium is an attempt to choose from the set of Nash Equilibria and in every subgame, a Nash Equilibrium will be kept due to the structure of the game. A Nash Equilibrium is a normal-form concept, which ignores the sequential structure of play in extensive-form games. As a

result it predicts some equilibria which appear problematic in the extensive form. But, Subgame Equilibrium can avoid these problems by reaching a local optimal.

In this paper, a game-theoretic negotiation scheme based on Subgame Equilibrium is used to guide a negotiation for sensor assignment to protect the maximum interest of every party during sensor assignment. The scheme is based on our recent work [14] and the work of Xiong *et. al*. [15]. We modify the scheme proposed in [14] by incorporating geometric feature into sensor assignment (see Section 2.3) and extending the geometric feature-aided scheme to multi-target cases (see Section 2.4).

To better understand the details of the game-theoretic negotiation, we discuss a scenario which has two targets and N sensors for a target tracking system. In the proposed scheme, two agents, named Agent 1 and Agent 2, are constructed to represent the responsibility of target tracking for the two targets respectively. In the initiation stage, the system sensors have been allocated to the two agents for target tracking. Now, if we want to increase the tracking accuracy on one of the targets (such as Agent 2), we need to ask for more resources (sensors) from other agents (such as Agent 1). If Agent 1 gives some resources to Agent 2 by the request from Agent 1, it will lead some loss of precision on target tracking responded by Agent 1. Thus, there is a need to find an agreement point between Agent 1 and Agent 2 by negotiation. There are two actions as the results of a negotiation. One is agreement which be reached at time $t \in T$. Another outcome is to capture all resources of the asked agent by the requesting agent or do nothing after the disagreement. Assume S is the set of the total resources and T is the time of the negotiation, three factors need to be considered during the negotiation:

• **Sensor information gain**: we name the difference of covariance of state estimates before and after measurements as *sensor information gain* [15] denoted as $g(t)$. The bigger the $g(t)$ matrix, the smaller the updated covariance will be.

$$g(t) = \left\| \sum_{i \in S} H_i^T R_i^{-1} H_i \right\| \tag{1}$$

where ‖ ‖ is the 2-norm of the sum of information gain to Sensor set S. From Eq. (1), we can see that $g(t)$ is increased by including more and better sensors in the combination S. $g(t)$ provides a convenient objective function that can be utilized as a basis for sensor allocation strategy and negotiation.

• **Utility**: For $\{S, T\}$, information gains of sensors will be considered as the basis of the utility values. Therefore, we denote (A_1, A_2) as the utility values of the agreement which assigns sensor subsets A_1 and A_2 to Agent 1 and Agent 2 respectively. (B_1, B_2) is denoted as the utility values of the agents before negotiation. We have the following property:

$$A_1 \cup A_2 = B_1 \cup B_2 \tag{2}$$

$$\left\| \sum_{i \in A_1} H_i^T R_i^{-1} H_i \right\| < \left\| \sum_{i \in B_1} H_i^T R_i^{-1} H_i \right\| \tag{3}$$

$$\left\| \sum_{i \in A_2} H_i^T R_i^{-1} H_i \right\| > \left\| \sum_{i \in B_2} H_i^T R_i^{-1} H_i \right\| \tag{4}$$

The average utility value during the time T from the beginning of the negotiation until its completion, which is denoted as $C(A, T)$, can be calculated by the follows:

$$C_1(A_1, t) = \frac{T \times \left\| \sum_{i \in B_1} H_i^T R_i^{-1} H_i \right\| + \left\| \sum_{i \in A_1} H_i^T R_i^{-1} H_i \right\|}{T + 1} \tag{5}$$

$$C_2(A_2, t) = \frac{T \times \left\| \sum_{i \in B_2} H_i^T R_i^{-1} H_i \right\| + \left\| \sum_{i \in A_2} H_i^T R_i^{-1} H_i \right\|}{T + 1} \tag{6}$$

• **Gain and Loess during negotiation**: For any $t_1, t_2 \in T$ and agreement $G = (A_1, A_2)$, if t_1 and t_2 are the time instances before and after negotiation respectively, we will have $C_1(A_1, t_1) \geq C_1(A_1, t_2)$ and $C_2(A_2, t_1) \leq C_2(A_2, t_2)$. During the negotiation, the operation of opting out will be performed as a force to achieve a quick agreement. If Agent 2 applies “opting out” at time t during negotiation, it will prevent Agent 1 from using its resources from time t to $t+k$, and ending at time $t+k+1$. During the period, all resources (sensors) of Agent 1 will be occupied by Agent 2. The utility after opting out for both agents can be expressed as:

$$C_1(opt, t) = \frac{t \times \left\| \sum_{i \in B_1} H_i^T R_i^{-1} H_i \right\|}{t + k + 1} \tag{7}$$

$$C_2(opt, t) = \frac{(t+k) \times \left\| \sum_{i \in B_2} H_i^T R_i^{-1} H_i \right\| + \left\| \sum_{l \in B_1 \cup B_2} H_i^T R_i^{-1} H_i \right\|}{t + k + 1} \tag{8}$$

2.3 Geometric feature-aided bargaining strategy for sensor assignment

In real-life target detection and tracking, the distance between the sensor and the target of interest acts a very

important role for sensing data quality. Signal-to-noise ratio (*SNR*) of the sensing data is largely decided by the distance. For radar, the received *SNR* can be expressed as:

$$SNR = \sigma C_{system} / R^4 \tag{9}$$

where C_{system} is a function of the radar system design parameters, R is the working distance between the target and radar. From the above expression, we can see that when the working distance between the target and radar increases the *SNR* of the sensing data will decrease accordingly. For EO/IR sensors, both *SNR* and the visual features (e.g. size, shape, texture, color, etc.) of the target will be decreased/ or dismissed in the acquired images/videos when the distance becomes longer.

During the negotiation of sensor assignment between two agents, every agent wants to receive the resources (sensors) close to its target, and thus to have good *SNR* data for target detection and tracking. For multi-sensor fusion, the geometric insight is already introduced by Kadar [18] to consider the sensor placement as a function of geometry induced error dilution. For the current SM methods, including our work reported in [14], the range of a target to a sensor is neither considered nor discussed explicitly. Since our method presented in [14] only uses sensor information gain (see Eq. (1)) of a sensor for sensor assignment and the value of sensor information gain of our selected sensor models is not sensitive to the distance varying between the sensor and a target, the proposed game-theoretic sensor assignment method does not consider the range factor between the sensor and a target. In this paper, we revise the bargaining strategy described in [14] to include the range information in and thus make our SM approach more efficient and practical for real-life applications. The revised bargaining strategy is named *geometric feature-aided game theoretic (GFGT) scheme*.

In negotiation, the strategy of each agent is utilized by agents to maximize its expected utility value. A strategy of an agent is its essential function and specifies what actions the agent will do after receiving a proposal from other agents, i.e., its proposal in the turn to make n counteroffer to others. In our GFGT scheme, a strategy profile of each agent is a collection of strategies of all agents involved in the game. We aim to develop rational bargaining strategies guided by subgame Nash Equilibrium and one geometric feature (the range information of a target to a sensor) to obtain an outcome that is profitable for both parties and where nobody can get better offer by using another strategy.

To make the description more concise, we assume there are two agents (the receiver and the caller) for negotiation at time t and denote them as A_1 and A_2 respectively. The negotiation consists of possible, utility, and competition (three notions) and can be expressed mathematically from Eq. (10) to Eq. (14).

$$Poss(t) = \{A = (A_1, A_2) \mid C_2(A_2, t) > C_2(opt, t)\} \tag{10}$$

where *Poss*(*t*) is a set of offers which are better than the opting-out for the receiver at time *t*.

For each offer, we calculate the range information between the target and the *i*th sensor by the follows:

$$D_i = \|P_i\|_2 \tag{11}$$

where P_i is positive definite and expressed as:

$$P_i = \begin{bmatrix} x_i^2 & x_i y_i \\ x_i y_i & y_i^2 \end{bmatrix}$$

where x and y are the distance between the target and the *i*th sensor in x-axis and y-axis direction respectively.

$$D_1(A_{1,b}(t), t) = \min_{A \in Poss(t)} D_{1,i}(A, t) \;\; A_{1,b}(t) \in Poss(t) \tag{12}$$

where $A_{1,b}(t)$ is the offer with the minimum geo-distance for Agent 1 in *Poss*(*t*) at time *t*.

$$D_2(A_{2,b}(t), t) = \min_{A \in Poss(t)} D_{2,i}(A, t) \;\; A_{2,b}(t) \in Poss(t) \tag{13}$$

where $A_{2,b}(t)$ is the offer with the minimum geo-distance for Agent 2 in *Poss*(*t*) at time *t*.

$$Compet(t) = \{A \in Poss(t) \mid A_{1,b}(t) > A_{2,b}(t)\} \tag{14}$$

where *Compet*(*t*) is the process to select a counter offer for the caller. During the entire process, the benefits of both the receiver and the caller will be guaranteed.

Bargaining strategy: When Agent 2 (the caller) constructs a proposal for Agent 1 (the receiver) due to situation changes (e.g. the movement of the mobile sensor or target, situation change of the inspected battlefield), the bargaining procedure of Agent 1 and Agent 2 will be started to complete a negotiation between them.

Step 1: At time *t+1*, Agent 1 has to make up a counteroffer to Agent 2 to maximize its own utility but prevent Agent 2 from performing opting out. Agent 1 will first calculate *Poss*(*t*) to get a set of possible offers for Agent 2, and estimate $D_1(A_{1,b}(t), t)$ and $D_2(A_{2,b}(t), t)$ for time *t*.

Step 2: Agent 1 calls *Compet*(*t*) to select the counteroffer for Agent 2 at time *t*. During the selection, the subgame equilibrium will be followed to maximize the benefits of both Agent 1 and Agent 2. The counteroffer should have no confliction with $A_{1,b}(t)$ and should have maximum overlap with $A_{2,b}(t)$. Then, Agent 1 will propose the offer $A^* \in Compet(t)$ and sent it to Agent 2. The process can be described as:

$$A^*(t) = \max_{A \in Cmpet(t)} \{A \mid A \to A_{2,b}(t), A \cap A_{1,b}(t) = \Phi\}$$

Step 3: Agent 2 will accept the offer from Agent 1 and jump to **Step 5**.

Step 4: If *Compet*(t)is empty, Agent 1 will propose a counteroffer, $A_{2,b}(t)$, to Agent 2 to protect the long-term benefits of both of them. Agent 2 will accept the counteroffer proposed by Agent 1.

Step 5: Sensors are reassigned and the negotiation is finished.

2.4 Extension to multiple targets

In real-life scenes, there are usually more than two targets (agents) for a STID system. We need to extend our GFGT scheme from two-agent negotiation to the negotiation of more than two agents (targets). For an agent needing resources from others, it is necessary to provide a candidate list for the agent to avoid ad-hoc broadcast to its neighboring agents. To improve negotiation efficiency, we propose to generate a *priority queue* to organize the agents whose target is located in the same local area and set up one-to-one negotiations for these agents according to the queue. We first calculate the *satisfied level* for each agent at time t and put them into a priority (ascending) queue. The satisfied level of an agent is the difference between the desired covariance norm and its current covariance norm, which is named as *satisfied_level*. For example, *Satisfied_level(i)* means the satisfied value of agent (target) *i*. A negative value of *satisfied_level* for an agent means the desired level of the agent has already been achieved and also has some excessive resources for the need of other agents. A large positive value means the agent eagerly needs some resources from other agents.

To perform multi-target negotiation, we build up a priority queue first and perform a mating process to find the neediest agent and the agent with the most excessive resources, and make them to have a one-to-one negotiation for sensor reassignment. After the negotiation, the priority queue will be updated in time and a new pair of the neediest agent and the most excessive agent will be chosen for sensor reassignment. The whole process will continue until all agents are satisfied or no excessive resource is available for reassignment. The details of the procedure of the multi-agent negotiation are described as follows:

Procedure for Multi-agent Negotiations

New_pair() = Ø
CONTINUE = True
Build an Ascending Queue (AQ) by the statisfied_level(i).

Stage 1: Mating

While (CONTINUE)
Begin
$p = \arg\max_{i \in AQ}$ *satisfied_level*(i);
$q = \arg\min_{i \in AQ}$ *satisfied_level*(i);
If (p and q are very close to each other or p is close to 0)
CONTINUE = False;
else Insert pair (p,q) to New_pair;
Remove p, q from AQ
Endif;
End;

Stage 2: Negotiation

For p, q in New_pair();
Begin
Launch a negotiation from p to q;
If (agreement is reached by the negotiation)
Update sensor information by the new assignment;
Endif;
End;

Stage 3: Priority Queue

For the updated p, q in New_pair();
Begin
Remove p, q from New_pair();
Insert p, q to AQ by their new satisfied_level;
End

The function of Stage 1 plays the mating process to find the best agent pair from the *satisfied_level queue* and control the whole process. Stage 2 serves the one-to-one negotiation and updates the allocation with the results from the negotiation. Stage 3 will maintain *the priority queue* for the whole mating process.

There are two schemes to maintain a priority queue for sensor management.

Scheme #1: Each agent will collect the information of its neighboring agents whose target is located in the same local area frequently and maintain a priority queue for itself. The scheme is good for a small scale system.

Scheme #2: There are some special geo-distributed nodes in the sensor network. Each node will collect the information of the agents whose target is located in its area and use the information to maintain a priority queue to control these agents. An agent will communicate with one of these special nodes first before sending out a proposal. The scheme is good for a large scale system.

Both schemes can achieve local optimum for sensor assignment. If there is only one node to maintain the queue in the whole system, global optimum can be possibly achieved. But, in that single-node case the sensor management scheme will become a kind of CSM.

3 Experimental Results

Simulation tests have been designed to evaluate the proposed algorithm with realistic sensor models. This section is dedicated to demonstrate the use of the GFGT scheme to improve the accuracy of target tracking and satisfy different desired covariance and information levels. All tests reported in this section are controlled by the norm of the desired covariance matrix.

3.1 Sensor modeling

The targets used in the simulation are tracked by a suite of sensors with different physical characters and varying sensing abilities. The sensor models are linear and the measurements z_j follow the form:

$$z_j(k) = H_j x(k) + v_j(k) \tag{15}$$

where j indicates the sensor number, $v_j(k)$ is the measurement noise vector, which is white and Gaussian, and has covariance $R(k, j)$.

Three different types of sensors are selected:

(1) Out-of-plane (**OOP**) imaging sensor measures the x and y position of targets. Its H and R matrix can be expressed as:

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \tag{16}$$

$$R = \begin{bmatrix} \sigma_x^2 & 0 \\ 0 & \sigma_y^2 \end{bmatrix} = \begin{bmatrix} 0.2 & 0 \\ 0 & 0.2 \end{bmatrix} \tag{17}$$

(2) Long range scan (**LRS**) sensor measures the range $p(k)$ and the range-rate $\dot{p}(k)$, which can be expressed as:

$$p(k) = \sqrt{x^2(k) + y^2(k)} \tag{18}$$

$$\dot{p}(k) = \frac{1}{p(k)}(x(k)\dot{x}(k) + y(k)\dot{y}(k)) \tag{19}$$

$$z_j(k) = [p(k), \dot{p}(k)]' \tag{20}$$

Note that the actual range and range-rate measurements are nonlinear with respect to the target states. We use a linear model and assume sensor-to-target geometries are constant to simplify the simulation. *x* and *y* are the relative position (distance) of the sensor to a target. $\dot{x}$ and $\dot{y}$ are the relative velocity of the sensor to a target. We also assume the relative motions in *x* and *y* directions are independent. Their linearization can be written as: $\frac{\partial p}{\partial x} = \frac{x}{p}$, $\frac{\partial p}{\partial y} = \frac{y}{p}$, $\frac{\partial \dot{p}}{\partial x} = \frac{\dot{x}}{p} - \frac{(x\dot{x} + y\dot{y})x}{p^3}$, $\frac{\partial \dot{p}}{\partial \dot{x}} = \frac{x}{p}$, $\frac{\partial \dot{p}}{\partial y} = \frac{\dot{y}}{p} - \frac{(x\dot{x} + y\dot{y})y}{p^3}$, $\frac{\partial \dot{p}}{\partial \dot{y}} = \frac{y}{p}$. For simplification, $\frac{\partial \dot{p}}{\partial x}$ and $\frac{\partial \dot{p}}{\partial y}$ are set to zero [2]. Thus, the measurement matrix of *H* and *R* can be expressed as:

$$H = \begin{bmatrix} \frac{\partial p}{\partial x} & 0 & \frac{\partial p}{\partial y} & 0 \\ 0 & \frac{\partial \dot{p}}{\partial \dot{x}} & 0 & \frac{\partial \dot{p}}{\partial \dot{y}} \end{bmatrix} \tag{21}$$

$$R = \begin{bmatrix} 10.7 & 0 \\ 0 & 7.4 \end{bmatrix} \tag{22}$$

(3) Single target track (**STT**) radar sensor measures range and range rate, but has a lower variance compared with a LRS sensor.

$$H = \begin{bmatrix} \frac{\partial p}{\partial x} & 0 & \frac{\partial p}{\partial y} & 0 \\ 0 & \frac{\partial \dot{p}}{\partial \dot{x}} & 0 & \frac{\partial \dot{p}}{\partial \dot{y}} \end{bmatrix} \tag{23}$$

$$R = \begin{bmatrix} 2.91 & 0 \\ 0 & 2.1 \end{bmatrix} \tag{24}$$

Note that the values of *R*'s used in our simulations are given in [2].

3.2 Simulation tests

To test our proposed GFGT algorithm to multi-target cases, several tests for the case of 2-targets and 12-distriuted sensors and the case of 3-targets and 6-distributed sensors were performed. In these tests, the selected sensors are heterogenous and distributed in ROI randomly. Targets in ROI move in different directions and with different speeds. Because of the space limitation, only the tests for 3-targets and 6-sensors are selected for demonstration. The geometric placement of these sensors and the trace of these moving targets are illustrated in Fig. 2 and described in Table 8. To simplify the test complexity, we assume the measures of all sensors are in the same space (coordinate system) and have the same unit (m).

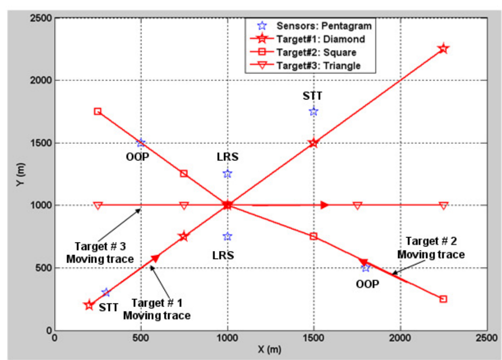

Fig. 2 Illustration of three moving targets and the distributed sensors

Table 1: Sensor table

Sensor #	Sensor Type	*x(m)*	*y(m)*
1	OOP	500	1500
2	OOP	1800	500
3	LRS	1000	1250
4	LRS	1000	750
5	STT	1500	750
6	STT	300	300

Tests: In these tests, 2 OOP, 2 STT, and 2 LRS sensors are placed randomly as illustrated in Fig. 2 in the initial stage. Two targets move in diagonal direction and one target moves horizontally. The desired covariance level of each target is updated at five different time instances: #1, #19, #39, #59, and #79 as listed in Table 9. When one update has happened, sensor reassignment will be evoked. The GFGT scheme will be called for sensor management. When the caller receives some resources (sensors) from the receiver, the tracking accuracy of the caller will be improved due the increase of sensor information gain. The

sensor negotiation will be repeated, until the norm of the current covariance matrix of the caller is close to the desired covariance level.

$$E(t) = \left\| P_d^{-1} \right\|_2 - \left\| \sum_{i \in S} H_i^T R_i^{-1} H_i \right\|_2 \qquad (25)$$

where S is the sensor set of the caller at Time t. $\left\| P_d \right\|_2$ is the desired error covariance level. When Eq. (25) is close to zero, negotiation is terminated. Here, we also assume agents can get the accurate estimation of target's position from the tracker before starting a new round of negotiations.

All the results after each update are illustrated in Fig. 3 to Fig. 8, and listed in Table 3 to Table 7.

Table 2: Desired Covariance Levels

Time	Target 1	Target 2	Target 3
1	1/5	1/10	1/20
19	1/15	1/15	1/6
39	1/15	1/15	1/15
59	1/10	1/15	1/7
79	1/10	1/10	1/20

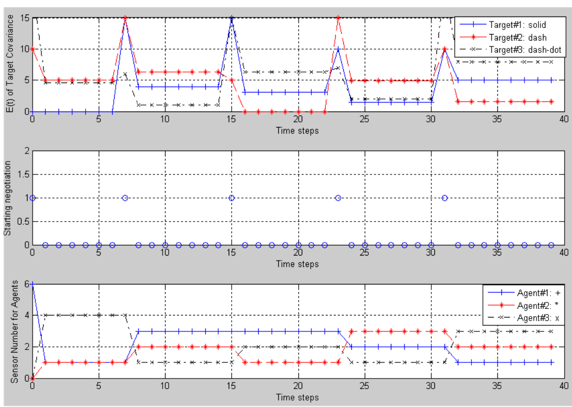

Fig. 3 Satisfying the desired covariance levels for all targets with different-type sensors (OOP, LRS, STT sensors)

Fig. 3 shows the situation changes when the desired covariance level is updated at five different time instances. At Time instance #1 (the initial stage), the covariance levels of Agent 1, Agent 2, and Agent 3 are set to 1/5, 1/10, and 1/20 respectively. All sensors are associated with Agent 1 initially. At Time instance #1, our GFGT algorithm begins to work and generates a priority queue for one-to-one negotiations. When this round of negotiations is completed, only one STT sensor is left for Agent 1 as its value of the desired covariance level is larger than the other two agents, which means Agent 1 does not need so many sensors for its tracking task. Agent 2 receives one OOP sensor which is the most geometrically-close sensor to Target #2. As Agent 3 has the biggest need for tracking, it receives three sensors from Agent 1 to satisfy its desired covariance level.

Since the number of sensors is limited, not all desired covariance levels can be satisfied completely as shown in the upper part of Fig. 3. The middle part of Fig. 3 shows at which time a round of negotiations is evoked. Here, we assume the round of one-to-one negotiations can be completed within one time-step. The bottom part of Fig. 3 shows the sensor reallocation results for different agents over time.

Table 3 Sensor assignment after Time instance #1

	OOP	LRS	STT
Target 1	0	0	1
Target 2	1	0	0
Target 3	1	2	1

Table 4 Sensor assignment after Time instance #19

	OOP	LRS	STT
Target 1	1	1	1
Target 2	1	0	1
Target 3	0	1	0

Table 5 Sensor assignment after Time instance #39

	OOP	LRS	STT
Target 1	1	2	0
Target 2	0	0	1
Target 3	1	0	1

Table 6 Sensor assignment after Time instance #59

	OOP	LRS	STT
Target 1	0	0	2
Target 2	1	2	0
Target 3	1	0	0

Table 7 Sensor assignment after Time instance #79

	OOP	LRS	STT
Target 1	0	0	1
Target 2	1	1	0
Target 3	1	1	1

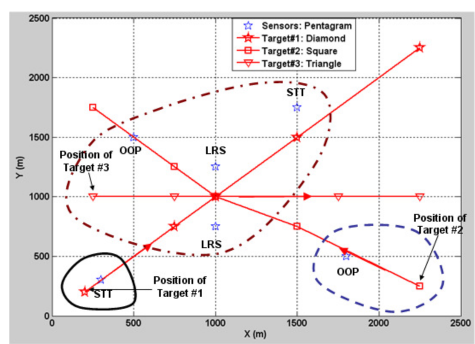

Fig. 4 Sensor assignment after Time instance #1

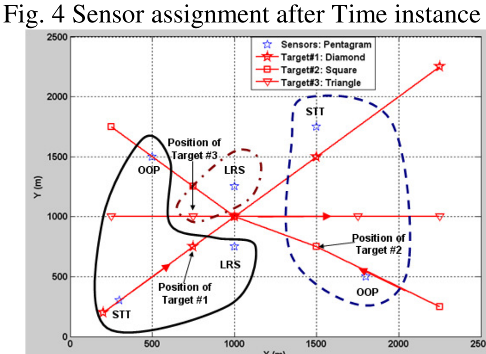

Fig. 5 Sensor assignment after Time instance #19

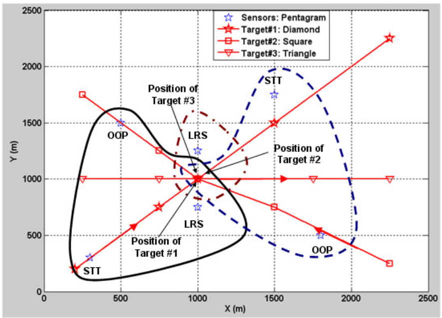

Fig. 6 Sensor assignment after Time instance #39

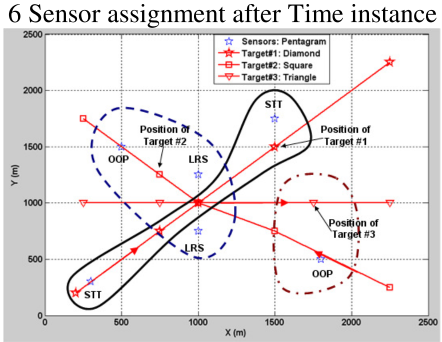

Fig. 7 Sensor assignment after Time instance #59

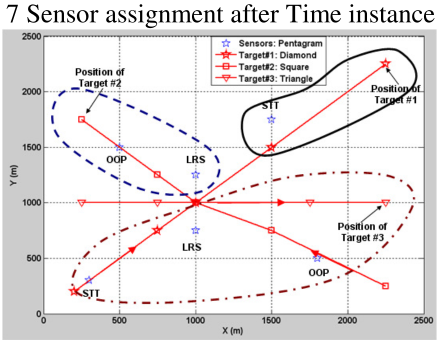

Fig. 8 Sensor assignment after Time instance #79

From the above Tables and Figures in Section 3, it can be seen that sensors will be reallocated to different agents based on the updated desired covariance levels. In the GFGT sensor assignment scheme, sensors are assigned by considering both their information gain and their current geometric placement of targets and sensors.

4 Conclusions

A geometric feature-aided game theoretic (GFGT) agent-based negotiable game theoretic sensor management (ANGSm) approach is presented for multiple sensor management. In the approach, subgame Nash Equilibrium is employed to protect benefits of all agents in negotiation. Both sensor information gain and the geometric feature of targets and sensors are incorporated in the bargaining strategy to make the proposed GFGT algorithm more efficient and practical. Simulation tests with three different sensor models have been performed. The test results demonstrate the applicability of the proposed approach. Our future work might include the performance comparison with other methods. Communication issues have not been addressed as we focused on studying the efficacy of GT methods as applied to DSM. These issues will be taken into account, along with the investigation of alternative DSM approaches, as future extensions of this paper

ACKNOWLEDGEMENTS

This research was supported in part by the US Air Force under contract number FA8650-08-C-1407. The views and conclusions contained herein are those of the authors and should not be interpreted as necessarily representing the official policies or endorsements, either expressed or implied, of the Air Force.

References

[1] M. K. Kalandros, L. Trailovic, L. Y. Pao, and Y. b. Shalom, "Tutorial on multisensory management and fusion algorithms for target tracking," Proceeding of the 2004 American Control Conference, pp. 4734-4748, 2004.

[2] M. Kalandros and L. Y. Pao, "Covariance control for multisensor systems," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 38, No. 4, Oct. 2002.

[3] W. Schmaedeke, "Information-based sensor management," *Proceeding of SPIE*, Vol. 1955, 1993.

[4] M. Wei, G. Chen, E. Blasch, H. Chen, and J.B. Cruz, Game Theoretic Multiple Mobile Sensor Management under Adversarial Environments," *Fusion 2008*, Cologne, Germany, 2008.

[5] J. Nash, "Optimal allocation of tracking resources," *Proceeding of IEEE Conf. on Decision and Control*, New Orleans, 1977.

[6] Y. Bar-Shalom and X. Li, Multitarget-Multisensor Tracking: *Principles and Techniques*, YBS Publishing, 1995.

[7] T. Kirubarajan, Y. Bar-shalom, W. D. Blair, and G. A. Watson, "LMMPDAF for Radar Management and Tracking Benchmark with ECM," *IEEE Trans. Aero. & Elect. Sys.*, Vol. 34, No. 4, 1995.

[8] G. A. Watson, W. D. Blair, and T. R. Rice, "Enhanced Electronically Scanned Array Resources Management through Multisensor Integration," *Proceedings of SPIE Conference Signal Processing of Small Target*, Vol. 3163, pp. 329-340, 1997.

[9] J. Manyika, An Information Theoretic Approach to Data Fusion and Sensor Management, PhD thesis, *The University of Oxford*, 1993.

[10] J. Manyikia and H. F. Durrant-Whyte, *Data Fusion and Sensor Management: An Information-Theoretic Approach*, Prentice Hall, 1994.

[11] B. S. Y. Rao, H. Durrant-Whyte, and A. Sheen, "A Fully Decentralized Multisensor System for Tracking and Surveillance," *International Journal of Robotics Research*, 12(1):20-45, 1991.

[12] S. Utete, A Network Manager for a Decentralized Sensing System, *Master's thesis*, University of Oxford, 1992.

[13] Durrant-Whyte, H. and M. Stevens, "Data fusion in decentralized sensing networks," *Int. Conference on Information Fusion*, 2001.

[14] X. Li, G. Chen, E. Blasch, J. Patrick, C. Yang, and I. Kadar, "Multi-Sensor management for data fusion in target tracking," *Signal Processing, Sensor Fusion and Target Recognition XVIII, Proc. SPIE Vol. 7336*, 2009.

[15] N. Xiong, H. Christensen, P. Svensson, "Reactive tuning of target estimate accuracy in multi-sensor data fusion," *An International Journal on Cybernetics and Systems*, Vol. 38, pp. 83-103, 2007.

[16] J. Nash, "Two-person cooperative games," *Econometrica*, Vol. 21, pp. 128-140, 1953.

[17] M. Osborne and A. Rubinstein, *A course in game theory*, Cambridge, Massachusetts: MIT Press, 1994.

[18] I. Kadar, "Optimum geometry selection for sensor fusion," *Proceedings of SPIE Conference on Signal Processing, Sensor Fusion and Target Recognition*, VII, 1998.

[19] I. Kadar, K.C. Chang, K. O'Connor and M. Liggins, "Figures-of-Merit to bridge fusion, long term prediction and dynamic sensor management", *Signal Processing, Sensor Fusion and Target Recognition XIII*, Ed. Ivan Kadar, Proc. *SPIE Vol. 5429*, 2004.